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Research paper

Sensitivity of WOFOST-based modelling solutions to crop parameters under climate change

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ABSTRACT

The formalization of novel equations explicitly modelling the impact of extreme weather events into the crop model WOFOST (EMS: existing modelling solution; MMS: modified modelling solution) is proposed as a way to reduce the uncertainty in estimations of crop yield. A sensitivity analysis (SA) was performed to assess the effect of changing parameters values on the yield simulated by the model (both EMS and MMS) for different crops (winter and durum wheat, winter barley, maize, sunflower) grown under a variety of conditions (including future climate realisations) in Europe. A two-step SA was performed using global techniques: the Morris screening method for qualitative ranking of parameters was first used, followed by the eFAST variance-based method, which attributes portions of variance in the model output to each parameter.

The results showed that the parameters related to the partitioning of assimilates to storage organs (FOTB) and to the conversion efficiency of photosynthates into storage organs (CVO) generally affected considerably the simulated yield (also underlying tight correlation with this output), whereas the parameters involved with respiration rate (Q10) or specific leaf area (SLA) became influential in case of unfavourable weather conditions. Major differences between EMS and MMS (which includes a component simulating the impact of extreme weather events) emerged in extreme cases of crop failure triggered by markedly negative minimum temperatures. With few exceptions, the two SA methods revealed the same parameter ranking. We argue that the SA performed in this study can be useful in the design of crop modelling studies and in the implementation of crop yield forecasting systems in Europe.

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1. Introduction

Crop models mathematically represent the complex interactions between plant, weather, soil and agricultural practices. They play an important role in understanding and quantifying the relationships, or trade-offs, between crop management and environment on one side, and cropping systems productivity on the other. Crop models have evolved over time, increasing in complexity to meet the increasingly intricate challenges facing agriculture (e.g. Donatelli and Confalonieri, 2011). For instance, the global carbon balance has become an issue of great societal concern in the last decades, when the global emission of CO_2 has continued to increase together with its impact on climate (IPCC, 2013). This has required modelling efforts, for instance, to represent plant responses to CO_2 levels (e.g. Ethier and Livingston, 2004) and thus make crop models responsive to changing climate conditions (Asseng et al., 2013; Bassu et al., 2014; Li et al., 2014). Nowadays, crop models are largely used to understand and anticipate the impacts of climate change on agricultural production (e.g. Ewert et al., 2005; Falloon and Betts, 2010; White et al., 2011; Supit et al., 2012; Nelson et al., 2014), to support the implementation of adaptation strategies (e.g. Tingem et al., 2009; Fernandes et al., 2012; Perego et al., 2014; Cappelli et al., 2015), and to design future crop ideotypes (e.g. Paleari et al., 2017).

However, robust simulation models are needed for diagnosing and prognosing the impacts of environmental factors on the crop

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production systems and, as a matter of fact, some modelling studies have not been completely successful in addressing the impact of extreme weather events on crop production (van der Velde et al., 2012; Zinyengere et al., 2014). Extreme events such as heat waves, cold shocks, droughts and frost affect directly and indirectly cropping systems by altering physiology and behaviour of plants, with impacts on the productivity as well as the seasonality and quality of crop production (e.g. Lesk et al., 2016). Moreover, the additional heat that is generated from ongoing temperature rise has increased the chances for severe heat waves, drought, and other forms of extreme weather (Field et al., 2012). Suggestions have been put forward that most of the existing crop models need an overhaul or an update as they often fail to correctly describe how crops respond to the impact brought about by extreme weather events (Rötter et al., 2011a).

Formalizing the biophysical interactions between the crop and its environment has required the development of customized modelling solutions (Luo et al., 2013) characterized by a large set of interdependent equations representing specific sub-domains of the system. Accounting for such complex interactions has inevitably increased the number of input factors in crop models (variables and parameters) and the uncertainties associated with parameter values and their distributional assumptions, driving variables (climate, soil and management) and model structure (e.g. Gabrielle et al., 2006). The structure of crop models is generally too complex to easily shed light on the relationship between input factors and output variables, even more so the models are continuously improved with novel approaches. Parameter estimation, in particular, is a key challenge in model development, in light of the crucial role in determining the quality of model predictions (Richter and Sondgerath, 1990). There is therefore a need to better understand the behaviour of crop models under a wide range of conditions, also by identifying the parameters that have the greatest influence on outputs (Jacquez and Perry, 1990; Brun et al., 2001; Haag, 2006).

Sensitivity analysis (SA) is the main tool for a comprehensive evaluation of complex models (e.g. Rabitz, 1989; Omlin et al., 2001). It assesses the changes in the model outputs due to changes in the values of input factors (the latter being generated by sampling from inputs' distributional range). As a result, SA provides a valuable method to identify properties that characterize the relationships between model outputs and input parameters and enhance the understanding of the system under study (Saltelli et al., 2000). The distinction – under specific conditions of application (Stearns, 1992) – between influential (relevant) and non-influential parameters is generally based on SA results (Cariboni et al., 2007; Confalonieri et al., 2009a). By ranking model parameters based on their relevance from the most to the least important (Cryer and Havens, 1999), SA offers guidance to the design of experimental programs as well as to more efficient model development and calibration. SA can be implemented either locally to examine the effect of minor variations of the parameter values on model results (Brun et al., 2001), or globally to consider the entire range of parameter values (Xu and Gertner, 2007; Confalonieri et al., 2010a). The latter is generally based on differential analysis through the use of Taylor series (e.g. Pastres and Ciavatta, 2005) and Monte Carlo methods (e.g. Annan, 2001). In particular, there is a challenge in ensuring robust modelling approaches under changing climate conditions, because the implicit assumption that well-designed and calibrated models under current conditions will remain valid under future climate realizations can be an unrealistic one. This is why the importance of improving the understanding of plant responses to the interactive effects of higher temperature and altered patterns of precipitation has been highlighted (e.g. Wang et al., 2012).

This study focused on the generic crop simulator WOFOST (van Diepen et al., 1989), successfully used since years to reproduce growth and development of a variety of crops (de Wit et al., 2012; Boogaard et al., 2013), to forecast crop yields (https://ec.europa.eu/jrc/en/mars), and within model intercomparison and ensemble studies (e.g. Todorovic et al., 2008; Palosuo et al., 2011; Bassu et al., 2014). In this study, we have performed a wide range of SA experiments on WOFOST using two versions of the model: an implementation referred to as existing modelling solution (EMS) and an improved model referred to as the modified modelling solution (MMS), with the latter including a software component (coupled to EMS) that explicitly takes into consideration the impacts of extreme weather events such as high and low temperatures, water deficit and frost (Villalobos et al., 2015). For both modelling solutions, SA was performed for five crops at eight sites representative of contrasting conditions in Europe (Italy, Spain, Switzerland and Ukraine) using two SA methods, and under current and altered weather conditions.

2. Materials and methods

2.1. WOFOST-based modelling solutions

WOFOST (van Diepen et al., 1989) adopts a gross photosynthesis approach to calculate net carbon fixation, explicitly considering phenological development, light interception, gross CO_2 assimilation, transpiration, growth and maintenance respiration. Crop development is reproduced as a temperature-driven process, optionally accounting for photoperiod. Instantaneous gross CO_2 assimilation (estimated at three moments in the day for three depths into the canopy of plant leaves) is computed on the basis of intercepted solar radiation and of a photosynthesis-light response at leaf level. Light interception depends on total incoming radiation, as modulated by photosynthetic leaf area and leaf angle distribution. Assimilates are partitioned to the various organs according to partitioning factors, computed as a function of plant development stage: a fraction of assimilates is allocated to roots first, and then the remainder is split over the above-ground organs (including below ground storage organs such as tubers). The emission of LAI units is driven by temperature in the early stages and it depends on specific leaf area and leaf-partitioned biomass later. Dead LAI units (i.e. leaves no more photosynthetically active) are quantified as a function of self-shading and senescence of old leaves. The model simulates both potential and water-limited production levels, providing information on crop water use, biomass growth and yield. Potential evapotranspiration is calculated via the Penman equation (Frère and Popov, 1979), and water stress is represented by the ratio of actual to potential transpiration. Crop water use is calculated separately for: crop canopy (transpiration), bare soil surface (soil evaporation), and soil surface with ponding (water evaporation).

The capability of the standard WOFOST version (EMS) was enhanced (MMS) thanks to a dedicated component for the impact of extreme weather events (Villalobos et al., 2015; Movedi et al., 2015). In particular, the effects of severe cold and high temperatures, frost and extreme water deficit on crop yields were accounted for by modulating the harvest index (HI) and LAI (only for frost) according to stress-related response functions (0 = maximum reduction; 1 = no effect) computed at a daily time step. These variations are mediated by the time of occurrence of an extreme event, the environmental conditions, and the crop-specific susceptibility. The decline of crop yield can even lead to crop failure in the case of severe extreme weather conditions. Two development phases are identified where crops are most sensitive to weather extremes: (i) around anthesis (+/− 1 week from anthesis) with main effects on pollen viability, fertilization, and grain formation, and (ii) from anthesis to physiological maturity, with impacts related to rates of grain filling. For temperature-related damages, crop temperature is estimated (solving the surface energy balance equation) and used.

Table 1
Location of the sites (with the relative crops) where sensitivity analysis was performed.

Country	Site	Latitude N (°)	Longitude E (°)	Elevation (m a.s.l.)	Crops
Spain	Cordoba	37.85	−4.80	100	Winter wheat, sunflower
	Granada	37.15	−3.00	650	Winter barley
Italy	Foggia	41.45	15.50	89	Durum wheat
Switzerland	Changins	46.40	6.23	455	Winter wheat; maize
	Ellighausen	47.60	9.13	508	Winter wheat; maize
	Reckenholz	47.43	8.52	444	Winter wheat; maize
	Therwil	47.50	7.54	316	Winter wheat; maize
Ukraine	Mironivka	49.66	31.00	155	Winter wheat; maize

The algorithms used to quantify the impact of weather extremes are fully documented in Appendix A.

2.2. Sensitivity analysis methods

The Morris screening method (Morris, 1991) as modified by Campolongo et al. (2007) was first applied to rank model parameters according to their influence on crop yield. Then, the extended version (eFAST, Saltelli et al., 1999) of the Fourier Amplitude Sensitivity Test method (FAST, Cukier et al., 1973) was applied to quantify the portion of the output variation due to changes in each parameter.

For the Morris method, the number of model runs for each SA experiment is equal to the number of trajectories (r) multiplied by (n + 1), with n being the number of parameters analysed. According to Confalonieri et al. (2010a), r was set equal to 5. The number of model runs (C) needed to complete a numerical experiment of SA with the eFAST method is equal to $C = n \cdot N_s$ with n being the number of parameters and N_s being the sample size. We obtained the convergence of sensitivity indices with $N_s = 330$, which is above the minimum value of 128 indicated by Wang et al. (2013), and represents a balanced solution between computational cost and the ability to explore the full parameter space.

The parameters related to light interception, gross photosynthesis, respiration, partitioning of photosynthates, leaf area expansion and senescence were subject to SA. Phenology-related parameters were not considered since they are limited in number and they are all potentially subject to local calibration (Confalonieri et al., 2010a). In WOFOST, a high number of parameters are organized in AFGEN (Arbitrary Function GENerator) tables, which describe the linear dependence of parameters (dependent variables) on average air temperature (Tavg) or development stage (DVS) (independent variables). The number of pairs (DVS, parameter value; Tavg, value), which constitute AFGEN tables, was reduced in order to avoid parameter distributions' overlap during samples generation (Confalonieri, 2010). Considering the relatively small number of parameters investigated (at most 31), all of them were analysed using both Morris and the eFAST methods. This allowed us to fully compare the results obtained with both SA methods.

2.3. Sensitivity analysis experiments

SA experiments were performed on five crops, i.e. winter wheat (*Triticum aestivum* L), durum wheat (*Triticum durum* Desf.), winter barley (*Hordeum vulgare* L), maize (*Zea mays* L.) and sunflower (*Helianthus annuus* L.), grown in eight experimental sites located in four European countries (Table 1). Parameters' description, distribution and related sources of information are presented in Appendices B, C and D.

Water-limited crop production was simulated, assuming unlimited nutrient supply and crops free from pests, diseases and weeds. Sowing and harvest dates were derived from local conventional farming practices.

Daily downscaled weather data (0.25° spatial resolution) for current climate conditions and future climate projections were used. Synthetic weather series were generated using two climate models – ICHEC-EC-EARTH KNMI-RACMO22E (van Meijgaard et al., 2008) and CNRM-CERFACS-CNRM-CM5 SMHI-RCA4 (Voldoire et al., 2013) – for the emission pathway scenario RCP8.5 (radiative forcing up to 8.5 W m^{-2} in 2100), which is the most extreme among those provided by the IPCC's Fifth Assessment Report (Moss et al., 2010; van Vuuren et al., 2011). Time slices of near past (1981–2010, with the exception of Spain, 1987–1999 and Switzerland, 1981–2014) and medium future (2041–2060) were considered. Fox Maule and Christensen (2015) describe the methods used in processing and post-processing the GCM/RCM outputs used in the generation of weather scenarios. The above methodology produced bias-corrected daily series of surface air temperature (minimum and maximum) and rainfall (different lengths of near-past time slices correspond to the varying observational data series used for bias-correction in different countries). Other variables needed to run the modelling solutions, such as global solar radiation, relative humidity and wind speed, were derived according to Duveiller et al. (2017). The beneficial effect of increasing CO_2 concentration on carbon assimilation rates was not considered in this study. The main reason for this choice is that the study was performed within a project (EU-FP7 MODEXTREME; http://modextreme.org) that targeted the WOFOST-based platform adopted by the European Commission to perform yield forecasts, which in its current version does not consider the effects of increasing atmospheric CO_2 concentration on crop productivity. Moreover, the effect of increasing CO_2 concentration on carbon assimilation rates in the presence of more frequent and intense extreme weather events is still controversial. This was highlighted by Long et al. (2006) and has been confirmed by two recent studies (Obermeier et al., 2016; Novak, 2017) demonstrating that CO_2 fertilization effects decline or even disappear as weather becomes drier and warmer.

For each combination crop × site, nine contrasting years were considered, three of them belonging to historical series and six belonging to projected weather series centred on 2050 at all sites. The nine years were selected to be sufficiently contrasting in terms of coldest-wettest, warmest-driest and average conditions, as represented by yearly-based agro-climatic indicators (Peterson et al., 2001; Barnett et al., 2006).

The range of climatic conditions represented by each scenario and time slice is shown in Fig. 1 by means of indicators of aridity and heat wave frequency. The possibility to discriminate between thermo-pluviometric conditions associated with aridity (b, De Martonne, 1942) gradients in the eight sites is given by the range published by Diodato and Ceccarelli (2004): $b < 5$: extreme aridity; $5 \leq b < 14$: aridity; $15 \leq b < 19$: semi-aridity; $20 \leq b < 29$: sub-humidity; $30 \leq b < 59$: humidity; $b > 59$: strong humidity. For identifying the frequency of heat wave (hw) days within a year in each site, we summarized the number of consecutive days (at least seven) when the maximum air temperature was higher than the average summer (June, July and August) max-

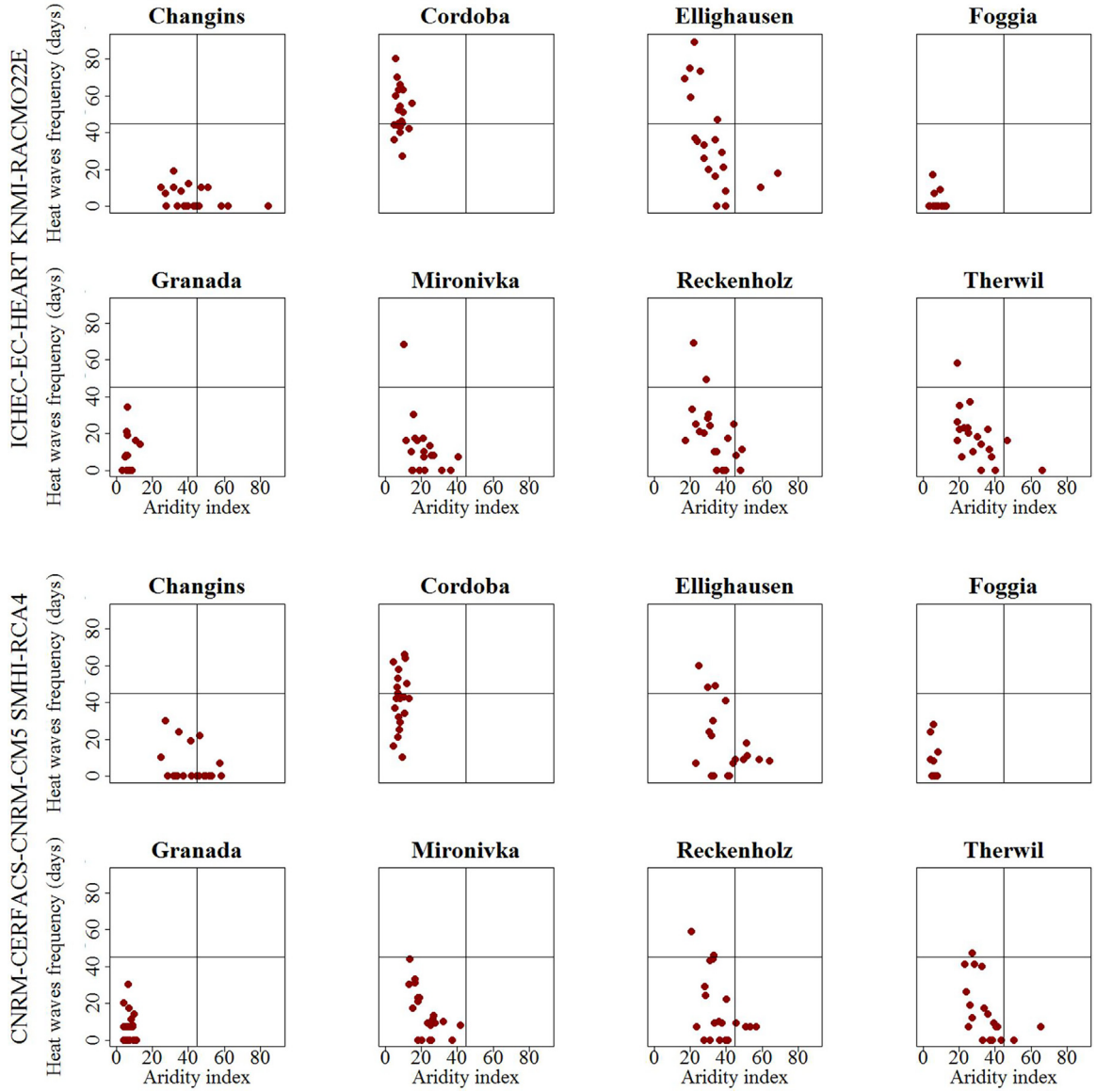

Fig. 1. De Martonne-Gottmann aridity index and heat wave days frequency calculated for each year of four weather scenarios and two periods, in a reference pixel for each study site.

imum air temperature of all the available years (baseline) +3 °C (Confalonieri et al., 2010b after Barnett et al., 2006). The range limits in this study were given by the minimum and the maximum numbers of the *hw* days of all sites and conditions (after Sándor et al., 2016): $hw \leq 14$: extremely moderate frequency; $14 < hw \leq 28$: very moderate frequency; $28 < hw \leq 42$: moderate frequency; $42 < hw \leq 56$: high frequency; $56 < hw \leq 70$: very high frequency; $hw > 70$: extremely high frequency.

3. Results and discussion

3.1. Sensitivity analysis results (eFAST method)

Fig. 2 shows the crop-specific variations of total sensitivity indices achieved by the top 10 ranked parameters across sites, years and modelling solutions considered.

The parameter involved with partitioning to storage organs (FOTB100 for wheat and barley and FOTB110 for maize) remerged as the most influential in yield simulations and the most sensitive to variations in the conditions explored (0.06 < Total sensitivity index < 0.59, median = 0.27). Conversely, the simulations of sunflower yield revealed the predominance of leaf dynamics- (SLATB000 and SPAN) versus photosynthesis- related parameters; the narrow range of variation of the total sensitivity index for both parameters denoted the primary role of temperature in limiting the leaf biomass conversion into leaf area at early crop stages regardless the site and year considered.

Focusing on winter wheat simulations in the Swiss sites, several influential parameters were identified. Parameters related with life span at 35 °C (SPAN), partitioning to storage organs at flowering (FOTB100), conversion efficiency into storage organs (CVO), extinction coefficient for diffuse light at flowering (KDIFTB100) and conversion efficiency into leaves (CVL) are distinctly identifiable by high values of the eFAST total sensitivity index (Fig. 3 and supplementary material from Fig. S1 to Fig. S3).

Certain balance in parameters ranking (i.e. the model is sensitive to several parameters) can be explained by the restrained meteorological variability which characterizes all the Swiss sites. Indeed, during the wheat cycle, temperatures rarely exceed 30 °C or drop below −8 °C. Moreover, water availability was always more than

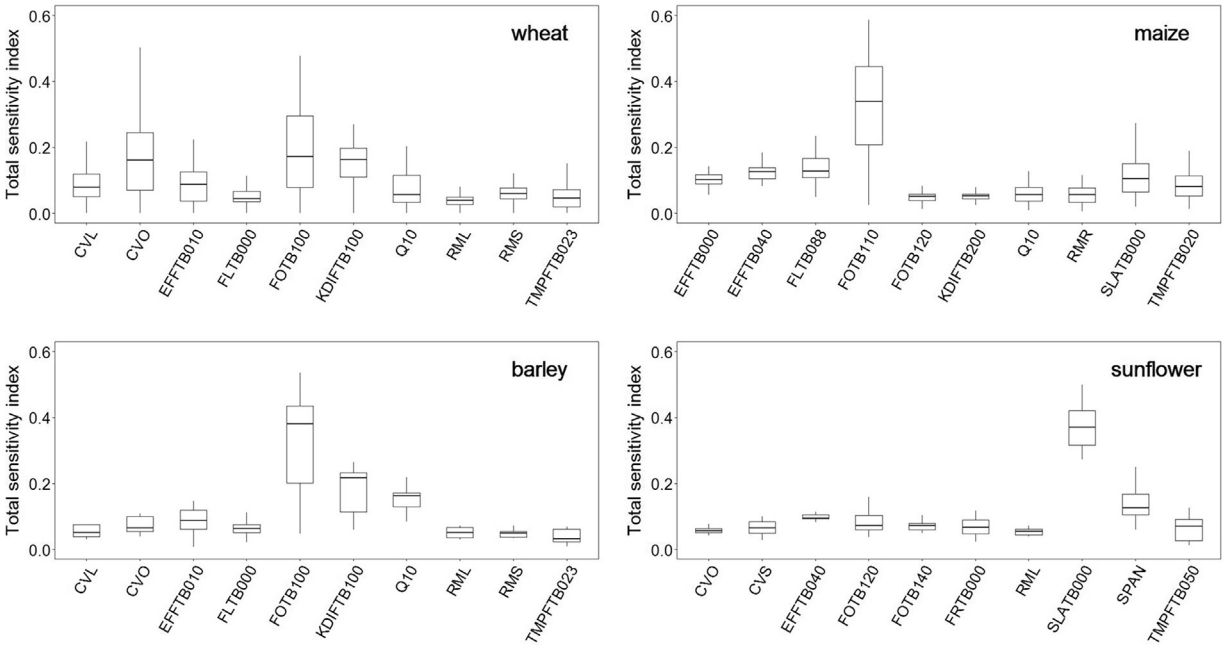

Fig. 2. Distributions of total sensitivity indices for each simulated crop. Results from durum and winter wheat simulations were processed together since the same parameterization was operatively used within the simulation experiment.

sufficient also in the years selected to represent warmest and driest conditions (>650 mm year^{-1} evenly distributed throughout the crop cycle). Substantial differences between modelling solutions emerged in three years out of nine, with MMS determining crop failure in the coldest and wettest year at all the Swiss sites due to the simulated effect of markedly negative minimum temperatures.

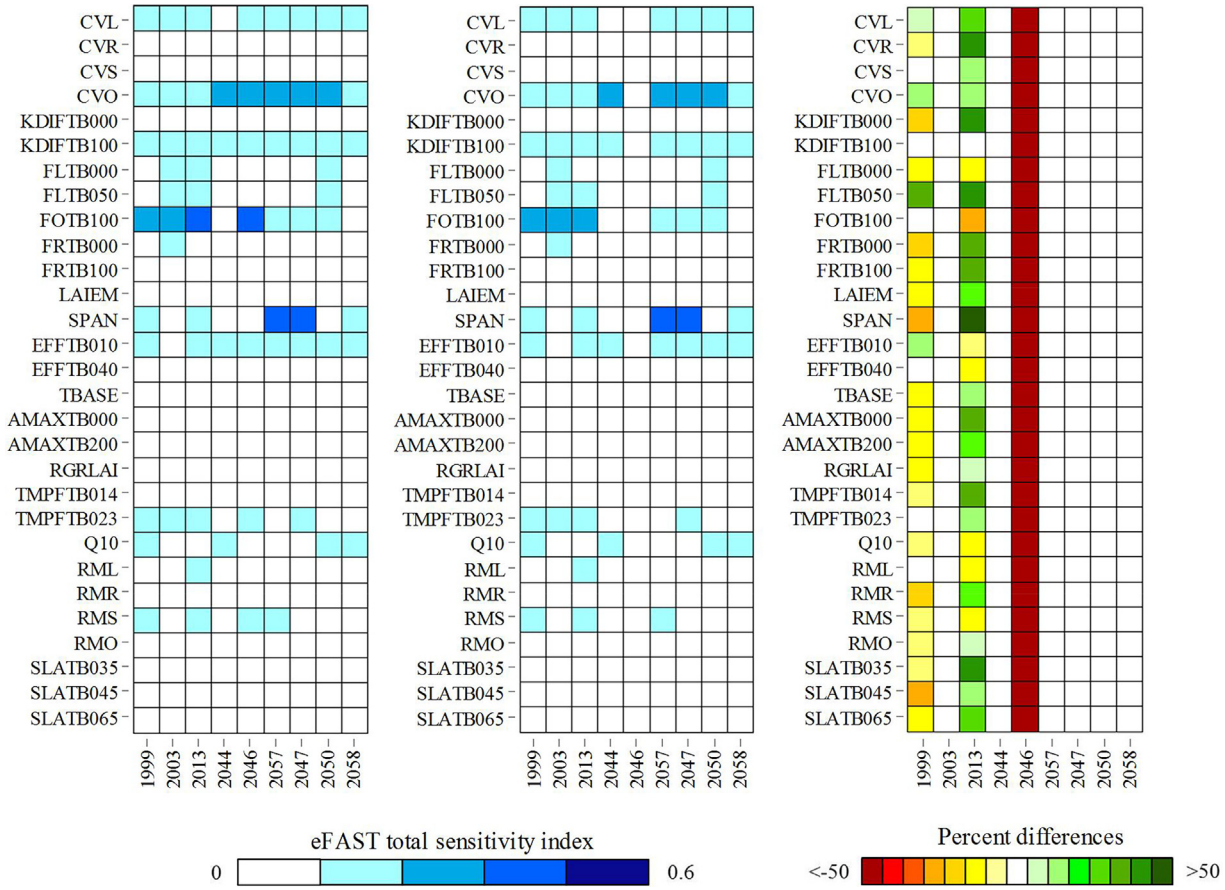

Fig. 3. eFAST total sensitivity index for winter wheat yield simulated with WOFOST at selected years in Switzerland (Changins site). Left panel = EMS (existing modelling solution); central panel = MMS (modified modelling solution); right panel = percent differences between the two modelling solutions.

These unexpected results underline the need to further adapt the component accounting for extreme weather events, which indicates very harmful impacts (i.e. crop failure) from a single day with minimum temperature below the threshold value for no damage at a time before hardening. A plausible solution to limit the frequency of frost shocks from single events could be the modulation of the crop response to temperature changes also considering the number of multiple consecutive days with extreme minimum temperature over the critical period (i.e. before hardening; Barlow et al., 2015).

The simulation of winter wheat in Mediterranean countries (Italy, supplementary material, Fig. S4; Spain, supplementary material, Fig. S5) provided quite different results. With few exceptions, FOTB100 was indicated as the most influential. In Spain, the parameter related with the relative increase in respiration rate per 10 °C (Q10) had the highest total sensitivity index in the warmest and driest growing seasons. In these years, due to high average temperatures and water scarcity, respiration rates are the factors that most affected crop growth and production (Tester and Langridge, 2010). In the other years, characterized by high amounts of rainfall and low average temperatures, CVO was instead the most influential. In these cases, the sub-optimal conditions led to a decrease in the partitioning to storage organs (Daniel and Triboi, 2002) and made CVO assuming the highest relevance.

Also in the Ukrainian site, CVO achieved high total sensitivity indices, with the exception of the years referring to the baseline time frame (i.e., 2004, 2005 2007; Supplementary material, Fig. S6). For these years, the parameter accounting for light use efficiency of single leaves at 10 °C (EFFTB010) emerged as the most influential. Indeed, the conditions for growing wheat in this country are less favourable owing to low levels of solar radiation. Moreover, for this site, the component accounting for extreme weather events determined crop failure in several years due to low minimum temperatures in winter (till −25 °C).

In a recent study, Ma et al. (2013) established, through the same sensitivity analysis technique, that AMAXTB130, SPAN and CVO are the most influential parameters when simulating winter wheat with WOFOST in the Hebei province of China. These information were profitably used by Huang et al. (2015, 2016) to calibrate WOFOST for the simulation of winter wheat in the same location and to identify the parameters to being re-initialized or re-calibrated to include in WOFOST remotely sensed data. The specific explored pedoclimatic conditions and the diverse varieties and crop management simulated led to different rankings among the parameters in the two studies, underlying the importance of performing sensitivity analyses before running models in a given operative context. Herein, the subset of WOFOST parameters to focus on was established according to the findings from previous studies carried out in European environments (van Diepen et al. (1988); Marletto et al. (2005); Priesack et al. (2006); Richter et al. (2010); Biernath et al. (2011); Rötter et al.(2011a, b); Stella et al. (2014)) while the limited number of points used in the AFGEN tables (E.g. AMAXTB 100 and 130 were not considered) aimed at reducing possible overlaps between the distributions assigned to parameters.

The ranking of parameters for maize simulations in Switzerland was the same at each site (supplementary material, from Fig. S7 to Fig. S10). The high values of the total sensitivity index associated with the parameter related with partitioning to storage organs right after flowering (FOTB110) underlined the key role of this parameter in simulating maize yield. This was not the case for maize simulations performed in Ukraine under the warmest and driest climate conditions, where yields were mostly influenced by specific leaf area at emergence (SLATB000; Supplementary material, Fig. S11). These years were characterized by a scarcity of water supply if compared with the others (on average 360 mm against 832 mm). This condition limited maize growth and made the simulation mostly influenced by the parameters related with the simulation of the early crop establishment (Subedi and Ma, 2009) rather than by those related with crop productivity at full canopy. The same rationale can be applied to the results achieved with sunflower simulation in Spain (Cordoba site; Supplementary material, Fig. S12). SLATB000 achieved the highest total sensitivity indices (up to three times higher than the second-ranked parameter) in all selected years and with both modelling solutions. In this case, sunflower production was limited by high temperatures, which caused a reduction in the CO_2 assimilation rate. This made SLATB000 the most influential parameter for sunflower yield simulation. The primary role of high temperatures in limiting crop growth and productivity is further underlined by the results achieved for the parameter SPAN (i.e. Life span of leaves growing at 35 °C), which denoted a higher value of total sensitivity index with the MMS rather than with the EMS.

The results of winter barley simulations in Spain (Granada site; Supplementary material, Fig. S13) identified FOTB100, extinction coefficient for diffuse light at flowering (KDIFTB100) and Q10 as the most influential parameters. Only in the coldest and wettest year of the baseline time frame (i.e. 1996), the parameters' ranking was slightly different. A reduction in the total sensitivity index achieved by FOTB100 was counterbalanced by an increased total sensitivity index for CVO. For this year, indeed, the high amount of rainfall and the low average temperatures determined a limited influence

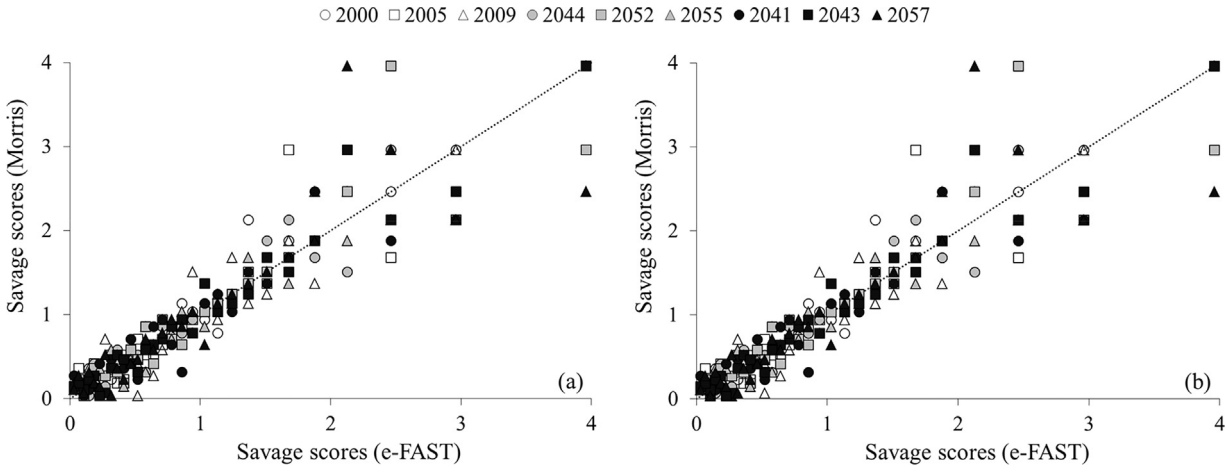

Fig. 4. Comparison between results obtained with the Morris and eFAST sensitivity analysis methods for with winter wheat simulation in Italy (Foggia site). a) = Savage Scores for the EMS (existing modelling solution); b) = Savage Scores for the MMS (modified modelling solution); dotted line = 1:1 line.

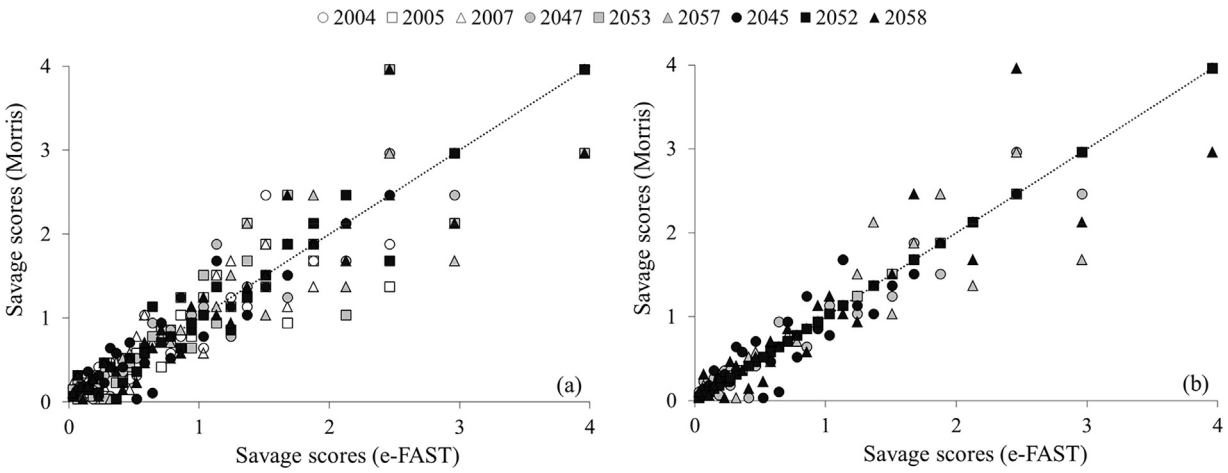

Fig. 5. Comparison between results obtained with the Morris and eFAST sensitivity analysis methods for winter wheat simulation in Ukraine (Mironivka site). a) = Savage Scores for the EMS (existing modelling solution); b) = Savage Scores for the MMS (modified modelling solution); dotted line = 1:1 line.

of the partitioning to storage organs in the simulation of crop yield (as already discussed for winter wheat simulations in Spain), which was mostly influenced by CVO.

3.2. Comparison between sensitivity analysis methods

The results obtained with the SA methods of Morris and eFAST were compared (Fig. 4 and 5 and supplementary material from Fig. S14 to Fig. S25) in terms of how they ranked parameters. In particular, the Savage Scores (Savage, 1956; Eq. (1)) were used to compare the parameters' sensitivity metrics achieved with the two methods, thus emphasising the ranking of the most influential parameters.

$$SV_{k,n} = \sum_{i=k}^{n} \frac{1}{i} \quad (1)$$

where $SV_{k,n}$ is the Savage Score for the k-ranked parameter of a set of n parameters.

For the eFAST method the Savage Scores were computed considering the total sensitivity index, whereas for the Morris method we focused on μ^*, which provides an indication of the overall influence of each parameter on the output.

The two methods provided similar parameter rankings, being the linear regression between Savage Scores calculated for the two methods significant ($p < 0.001$), with R^2 ranging from 0.61 to 0.98 considering all the values). Furthermore, the ranking calculated based on the two methods for each combination crop × site was the same for the two modelling solutions (EMS, Fig. 4a; MMS, Fig. 4b). Major differences between the two modelling solutions arose when the component simulating the impact of extreme weather events determined crop failure; in these cases, the correlation between parameter rankings was higher for the MMS. An example is provided by winter wheat simulations in the Ukrainian site (Fig. 5), where the complete yield losses in the coldest years were explained solely by variations in parameters involved with the effect of extreme negative temperatures on *HI* (all other parameters were not relevant). In the same years, results achieved for EMS led to major discrepancies in the ranking of model parameters (Fig. 5a), meaning that several parameters related to yield formation played a key role in explaining yield responses at suboptimal temperature for growth.

4. Conclusions

The results of this sensitivity study increase the knowledge about the behaviour of the crop model WOFOST in the simulation of the yield of different crops across several European sites under current conditions and projected scenarios of climate change. The simulated crop yield was mostly influenced by parameters related with storage organs. Indeed, although with some exceptions, the parameters involved in partitioning to storage organs around flowering (FOTB100–FOTB110) and conversion efficiency into storage organs (CVO) had the highest total sensitivity indices. Nevertheless, for sunflower simulations in Spain and maize in Ukraine, results were mainly influenced by specific leaf area at emergence (SLATB000), underlying the importance of early crop establishment in case of sub-optimal growth conditions. Some differences were observed between the results obtained for the two modelling solutions assessed in this study (i.e. EMS and MMS) in terms of both total sensitivity metrics and parameters' ranking, especially when the simulated impact of extreme weather events determined crop failure. The two SA methods (i.e. Morris and eFAST) provided similar parameters' rankings. This confirms the usefulness of the Morris method (which is less demanding in terms of computational time) for identifying the most influential parameters, and its suitability for screening purposes before the application of variance-based methods (computationally-expensive) in 2-step SA designs.

These results also indicate the need to further improve the component simulating the impacts of extreme weather events, owing to its tendency to sometimes overestimate the impact of weather extremes.

The SA experiments led to identify the most influential parameters for the simulation of several crops across European sites, spreading useful information to achieve the best trade-off between parameterization effort and reliability of model estimates. The coupling of the WOFOST model with the component simulating the impacts of extreme weather events and its application under climate change scenarios lays the basis to improve the in-season crop growth monitoring and yield forecasting capabilities at EU level in the short and medium term. Indeed, the crop yield forecasting system of the European Commission lacks a dedicated module to consider the effects of climatic shocks or extreme events on yield formation. This limit could even be exacerbated in the near future due to the likely increase in the frequency of climatic extremes due to climate change (EEA, 2017). The development of an early forecasting and warning system more adherent to real conditions can thus be a valuable support to multiple stakeholders of the agri-

cultural sector in ensuring citizens health protection, crop needs and environment preservation according to local priorities and national/European regulations. As noted, details about the effect of increasing atmospheric CO_2 concentration go beyond the aim of this study. However, as a natural evolution of what has already been presented, dedicated routines can be arranged and implemented with the purpose of testing CO_2 effects within the European Commission (Crop Growth Monitoring System; https://ec.europa.eu/jrc/en/mars) version of WOFOST.

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Appendix A. Key processes and modelling approaches for the impact of extreme events

General framework

For each day around anthesis, the overall value of the response function to temperature (as driven by mean crop temperature) and water stress is calculated using the following equation:

$$F = \frac{1}{day}\sum_{i}^{day} min\left(F_T, F_W\right) \tag{2}$$

where F (−) is the response function to crop temperature and water stress; F_T (−) is the response function to average crop temperature; F_W (−) is response function to extreme water stress. In addition, the effect of frost (function of minimum crop temperature) and extreme heat (function of maximum crop temperature) are computed as:

$$F_A = F \cdot \prod_{1}^{day} min\left(F_F, F_H\right) \tag{3}$$

where F_A (−) is overall response function to stresses; F_F (−) is the response function to frost; F_H (−) is the response function to extreme heat. Then, the actual maximum HI that might be attained after anthesis is completed (HIAA, −) is computed as:

$$HI_{AA} = F_A \cdot HI_{max} \tag{4}$$

where HI_{max} (−) is the potential HI for the specific species.

From anthesis to maturity, the component assumes that the HI increases linearly from zero to HIAA, so the final HI is computed according to Eq. (5):

$$HI = \frac{HI_{AA}}{d_{PA}} \cdot t \tag{5}$$

where HI (−) is the final HI; d_{PA} (d) is duration of the phase expressed as calendar days; t (d) is the time after anthesis expressed as calendar days.

Any frost or heat event occurring during this period (e.g. at time t_1) has an impact calculated according to Eq. (6):

$$HI = HI_{AA} \cdot \left[\left(1 - F_A\right) \cdot \frac{t_1}{d_{PA}} + F_A\right] \tag{6}$$

Response to extreme water stress

The extreme water stress can be expressed as the cumulative reduction in transpiration since transpiration becomes limited. This limitation starts when the water content in the soil is equivalent to the concept of allowable depletion (Eq. (7)), which is the fraction of plant available water that can be extracted by the crop without negative effects on transpiration, assimilation or growth.

$$AD = 0.04 \cdot AD_5 \cdot \left(5 - ET_0\right) \tag{7}$$

where AD (mm) is the allowable depletion ($0.1 < AD < 0.8$); AD_5 (−) is a crop-specific parameter that increases or decreases AD (reference values: 0.55 for winter/durum wheat, winter barley, maize; 0.45 for sunflower); ET_0 (mm) is the reference evapotranspiration.

For a given value of relative transpiration (i.e., actual to reference evapotranspiration ratio), the cumulative reduction in crop transpiration (f_R) since the onset of water deficit is:

$$f_R = \left(1 - r\right)^2 \cdot \left(1 - AD\right) \tag{8}$$

where r (−) is the relative transpiration.

So the fraction of unreduced transpiration (f_E, −) is equal to:

$$f_E = 1 - \left(1 - r\right)^2 \cdot \left(1 - AD\right) \tag{9}$$

The response function to severe water stress is thus computed according to Eq. (10) and is set to one when it exceeds the crop-dependent parameter f_{Ecrit} (reference value: 0.7 for winter/durum wheat, winter barley, maize; 0.8 for sunflower):

$$F_w = \frac{f_E}{f_{Ecrit}} \tag{10}$$

Response to heat

The response to heat (i.e. F_H; Eq. (11)) is computed as a function of maximum canopy temperature (T_{max}) and is equal to one when maximum crop temperature does not exceed a minimum damage threshold (T_{XC}). For high values, F_H decreases linearly to zero when an upper limit canopy temperature is reached (T_{X0}, °C):

$$F_H = \begin{cases} 1 & T_{max} \le T_{XC} \\ \dfrac{\left(T_{max} - T_{X0}\right)}{\left(T_{XC} - T_{X0}\right)} & T_{XC} < T_{max} < T_{X0} \\ 0 & T_{max} \ge T_0 \end{cases} \tag{11}$$

where T_{max} (°C) is the daily maximum canopy temperature; T_{XC} (°C) is the temperature below which no heat stress occurs during reproductive phase; T_{X0} (°C) is the critical temperature at which the effect of heat stress on HI is maximum.

Response to frost

The simulation of the crop response to frost is described using two distinct equations accounting for the impacts on harvest index (F_{F1}, Eq. (12)), and LAI (F_{F2}), as:.

$$F_{F1} = \begin{cases} 0 & T_{min} \le T_{100} \\ \dfrac{(T_{min} - T_{100})}{(T_0 - T_{100})} & T_{100} < T_{min} < T_0 \\ 1 & T_{min} \ge T_0 \end{cases} \quad (12)$$

where $T_{\min}$ (°C) is the minimum daily canopy temperature; T_0 (°C) is the critical temperature below which flower/grains number begins to reduce; *T100* (°C) is the critical temperature at which flowers/grain number is zero [°C]. The algorithm computing the frost impact on photosynthetic tissues (F_{F2}) is formally the same as the one used for *HI*, but the critical killing temperatures are referred to the number of dead leaves (as fraction of total LAI) instead of the number of flowers/grains.

Calculation of maximum canopy temperature

The maximum canopy temperature ($T_{\max}$; °C) is computed as:

$$T_{max} = T_a + [(1 - f_G) \cdot R_n - LE] \cdot \frac{r_{aH}}{\rho \cdot C_p} \quad (13)$$

where T_a (°C) is the maximum daily air temperature; f_G (−) is the fraction of net radiation invested in soil heat flux (assumed equal to 0.1 during daytime); R_n (W m^{-2}) is the net solar radiation; *LE* (W m^{-2}) is the latent heat flux; r_{aH} (s m^{-1}) is the aerodynamic resistance; ρ (kg m^{-3}) is the air density; C_p [J kg^{-1} °C^{-1}] is the specific heat of air.

Calculation of minimum canopy temperature

The minimum canopy temperature ($T_{\min}$) is computed as:

$$T_{min} = \frac{(1 - f_G) \cdot [-\varepsilon_v a + \varepsilon_a a + \varepsilon_a b T_{aw}] \cdot r_a \gamma^* + \rho C_p T_a (\Delta + \gamma^*) - D}{\rho C_p \cdot (\Delta + \gamma^*) + (1 - f_G) \gamma^* r_a \varepsilon_v b} \quad (14)$$

where: γ (0.067 kPa K^{-1}) is the psychrometric constant; γ^* (kPa K^{-1}) is equal to $\gamma(1+r_c/r_a)$; D (kPa) is the vapor pressure deficit; T_{aw} (°C) is the air temperature measured at weather station; Δ [kPa K^{-1}] is the slope of saturation vapor pressure versus temperature; Δ' (kPa K^{-2}) is the slope of Δ versus temperature; r_c (s m^{-1}) is the canopy resistance [700 s m^{-1} for dry canopies, 0 s m^{-1} for wet canopies]; r_a (s m^{-1}) is the aerodynamic resistance at a reference crop height of 0.12 m and at a standardized height for temperature, wind speed and humidity measurement (2 m above soil surface); ε_v and ε_a (−) are the emissivity of vegetation and of the atmosphere; a and b are coefficients of the linear form of the Stefan-Boltzmann equation.

Appendix B. WOFOST parameters used for winter wheat and winter barley and statistical settings used for sensitivity analysis (SA). Parameters with the field "Value" populated were not used for SA. For TSUM1 and TSUM2, first value refers to wheat, the second to barley.

Parameter	Units	Value	Mean	Stand. dev.	Source[d]
Base temperature for emergence (TBASEM)	°C	0			1
Maximum effective temperature for (TEFFMX)	°C	30			1
Thermal sums to reach emergence (TSUMEM)	°C-d	50			1
Daily increase in temperature sums (DTSMTB) at Tavg[a] = 0	°C;°C-d	0			1
at Tavg = 10		10			1
at Tavg = 18		20			1
at Tavg = 24		24			1
at Tavg = 28		21			1
at Tavg = 30		13			1
at Tavg = 31		0			1
Thermal sums from emergence to anthesis (TSUM1)	°C-d	1700			1
Thermal sums from anthesis to maturity (TSUM2)	°C-d	850			1
Leaf area index at emergence (LAIEM)	ha ha^{-1}		0.137	0.0068	1
Maximum relative increase in leaf area index (RGRLAI)	ha ha^{-1} °C^{-1} d^{-1}		0.01	0.0004	2, 3
Specific leaf area (SLATB) at DVS[b] = 0	-; ha kg^{-1}	0.002			2, 3
at DVS = 0.35			0.022	0.0001	1
at DVS = 0.45			0.002	0.0001	2, 3
at DVS = 0.65			0.002	0.0001	1
at DVS = 2.00		0.002			1
Specific pod area (SPA)	ha kg^{-1}	0			1
Specific stem area (SSATB) at DVS = 0	ha kg^{-1}	0			1
at DVS = 2		0			1
Life span of leaves growing at 35 °C (SPAN)	d		35	1.75	2, 4
Base temperature for leaf aging (TBASE)	°C		0	0.05	3, 5, 6
Extinction coefficient for diffuse light (KDIFTB) at DVS = 0	-;-		0.4	0.03	2, 3
at DVS = 0.65		0.4			1
at DVS = 1			0.6	0.03	2, 3
at DVS = 2		0.65			1
Light use efficiency single leaf (EFFTB) at Tavg = 0	kg	0.6			1
at Tavg = 10	ha^{-1} h^{-1} J^{-1} m^2 s		0.6	0.03	2, 5, 7
at Tavg = 40			0.6	0.03	2, 5, 7
Maximum CO_2 assimilation rate (AMAXTB) at DVS = 0	-;kg ha^{-1} h^{-1}		36	1.79	3
at DVS = 2			23	0.22	2, 3
Reduction factor of AMAX (TMPFTB) at Tavg = 0	°C;-	0			1
at Tavg = 12		0.7			1
at Tavg = 14			0.92	0.05	3
at Tavg = 23			1	0.05	3
at Tavg = 28		0.9			1
at Tavg = 31		0.6			1
at Tavg = 33		0			1

Reduction factor of AMAX (TMNFTB) at Tmin[c] = 0	°C;-	0			1
at Tmin = 3		1			1
Efficiency of conversion into leaves (CVL)	kg ka^{-1}		0.685	0.034	2, 4
Efficiency of conversion into storage organs (CVO)	kg ka^{-1}		0.709	0.035	2, 4
Efficiency of conversion into roots (CVR)	kg ka^{-1}		0.694	0.035	2, 4
Efficiency of conversion into stems (CVS)	kg ka^{-1}		0.662	0.033	2, 4
Rel. incr. in respiration rate per 10 °C (Q10)	–		2	0.1	2, 3, 4
Rel. maintenance respiration rate for leaves (RML)	kg kg^{-1} d^{-1}		0.03	0.001	2, 4
Rel. maintenance respiration rate for storage organs (RMO)	kg kg^{-1} d^{-1}		0.01	0.0005	2, 4
Rel. maintenance respiration rate for roots (RMR)	kg kg^{-1} d^{-1}		0.015	0.0007	2, 4
Rel. maintenance respiration rate for stems (RMS)	kg kg^{-1} d^{-1}		0.015	0.0007	2, 4
Reduction factor for senescence (RFSETB) at DVS = 0	-;-	1			1
at DVS = 2		1			1
Partitioning to roots (FRTB) at DVS = 0	-;kg kg^{-1}		0.5	0.025	2, 3, 8
at DVS = 1			0.02	0.001	2, 3, 8
at DVS = 1.2		0			1
Partitioning to leaves (FLTB) at DVS = 0	-;kg kg^{-1}		0.65	0.032	2, 3, 8
at DVS = 0.5			0.5	0.025	2, 3, 8
at DVS = 0.85		0.1			1
at DVS = 1		0.01			1
at DVS = 2		0			1
Partitioning to storage organs (FOTB) at DVS = 0	-;kg kg^{-1}	0			1
at DVS = 0.75		0			1
at DVS = 0.82			0	0.01	2, 3, 8
at DVS = 1			1	0.059	2, 3, 8
at DVS = 1.22		1			1
at DVS = 2		1			
Partitioning to stems (FSTB) (function of DVS)	-;kg kg^{-1}	Derived as 1–(FLTB + FOTB)			
Relative death rate of roots (RDRRTB) at DVS = 0	-;kg kg^{-1} d^{-1}	0			1
at DVS = 1.5		0			1
at DVS = 1.5001		0.02			1
at DVS = 2		0.02			1
Relative death rate of stems (RDRSTB) at DVS = 0	-;kg kg^{-1} d^{-1}	0			1
at DVS = 1.5		0			1
at DVS = 1.5001		0.02			1
at DVS = 2		0.02			1

[a] mean air daily temperature.
[b] development stage code (0: emergence; 1: flowering; 2: maturity).
[c] minimum air daily temperature.
[d] 1: adapted from Stella et al. (2014); 2: van Diepen et al. (1988); 3: Richter te al. (2010); 4: Arora and Gajri (1998); 5: Marletto et al. (2005); 6: Priesack et al. (2006); 7: Biernath et al. (2011); 8: Rötter et al. (2011a, b).

Appendix C. WOFOST parameters used for maize and statistical settings used for sensitivity analysis (SA). Parameters with the field "Value" populated were not used for SA.

Parameter	Units	Value	Mean	Stand. dev.	Source[d]
Base temperature for emergence (TBASEM)	°C	10			1
Maximum effective temperature for (TEFFMX)	°C	30			1
Thermal sums to reach emergence (TSUMEM)	°C-d	40			1
Daily increase in temperature sums (DTSMTB) at Tavg[a] = 0	°C;°C-d	0			1
at Tavg = 8		10			1
at Tavg = 30		23			1
at Tavg = 35		23			1
Thermal sums from emergence to anthesis (TSUM1)	°C-d	1600			1
Thermal sums from anthesis to maturity (TSUM2)	°C-d	1100			1
Leaf area index at emergence (LAIEM)	ha ha^{-1}		0.372	0.0157	1, 2
Maximum relative increase in leaf area index (RGRLAI)	ha ha^{-1} $°C^{-1}$ d^{-1}		0.03	0.0145	1, 2
Specific leaf area (SLATB) at DVS[b] = 0	-; ha kg^{-1}		0.003	0.0064	3
at DVS = 0.5			0.002	0.0001	3
at DVS = 0.78		0.001			3
at DVS = 2.00		0.001			3
Specific pod area (SPA)	ha kg^{-1}	0			3
Specific stem area (SSATB) at DVS = 0	ha kg^{-1}	0			3
at DVS = 2		0			3
Life span of leaves growing at 35 °C (SPAN)	d		36.5	1	1–3
Base temperature for leaf aging (TBASE)	°C		9	1.41	1–3
Extinction coefficient for diffuse light (KDIFTB) at DVS = 0	-;-		0.6	0.03	2, 3
at DVS = 2			0.6	0.03	2, 3
Light use efficiency single leaf (EFFTB) at Tavg = 0	kg ha^{-1} h^{-1} J^{-1} m^2 s		0.475	0.0353	1–3
at Tavg = 40			0.2	0.01	1–3
Maximum CO_2 assimilation rate (AMAXTB) at DVS = 0			55	2.75	2, 3
at DVS = 1.25		50			3
at DVS = 1.5			40	2	2, 3
at DVS = 1.75		35			3
at DVS = 2			21	1.05	2, 3

Reduction factor of AMAX (TMPFTB) at Tavg = 0	°C;-	0			
at Tavg = 9		0			
at Tavg = 20			0.5	0.025	1–3
at Tavg = 30		1			1
at Tavg = 35			0.9	0.045	1–3
at Tavg = 42		0.078			1
Reduction factor of AMAX (TMNFTB) at Tmin[c] = 5	°C;-	0			1
at Tmin = 12		1			1
Efficiency of conversion into leaves (CVL)	kg ka^{-1}		0.7	0.028	1–3
Efficiency of conversion into storage organs (CVO)	kg ka^{-1}		0.695	0.035	1–3
Efficiency of conversion into roots (CVR)	kg ka^{-1}		0.705	0.021	1–3
Efficiency of conversion into stems (CVS)	kg ka^{-1}		0.674	0.023	1–3
Rel. incr. in respiration rate per 10 °C (Q10)	–		2	0.1	1, 2
Rel. maintenance respiration rate for leaves (RML)	kg kg^{-1} d^{-1}		0.03	0.0015	1–3
Rel. maintenance respiration rate for storage organs (RMO)	kg kg^{-1} d^{-1}		0.01	0.0005	1–3
Rel. maintenance respiration rate for roots (RMR)	kg kgkg^{-1} d^{-1}		0.013	0.0035	1–3
Rel. maintenance respiration rate for stems (RMS)	kg^{-1} d^{-1}		0.015	0.00075	1–3
Reduction factor for senescence (RFSETB) at DVS = 0	-;-	1			1
at DVS = 2		1			1
Partitioning to roots (FRTB) at DVS = 0	-;$kg^{-1}$$kg^{-1}$		0.4	0.02	1, 2
at DVS = 0.4			0.262	0.013	1, 2
at DVS = 1		0			3
at DVS = 1.2		0			3
Partitioning to leaves (FLTB) at DVS = 0	-;kg kg^{-1}		0.62	0.031	1, 3
at DVS = 0.5			0.52	0.031	1, 3
at DVS = 0.88			0.215	0.09	1, 3
at DVS = 1.2		0			3
at DVS = 2		0			3
Partitioning to storage organs (FOTB) at DVS = 0	-;kg kg^{-1}	0			1
at DVS = 0.9		0.2			1
at DVS = 1.1			0.63	0.18	1, 3
at DVS = 1.2			0.95	0.05	1, 3
at DVS = 2		2			1
Partitioning to stems (FSTB) (function of DVS)	-;kg kg^{-1}	Derived as 1–(FLTB + FOTB)			
Relative death rate of roots (RDRRTB) at DVS = 0	-;kg kg^{-1} d^{-1}	0			3
at DVS = 1.5		0			3
at DVS = 1.5001		0.02			33
at DVS = 2		0.02			3
Relative death rate of stems (RDRSTB) at DVS = 0	-;kg kg^{-1} d^{-1}	0			3
at DVS = 1.5		0			3
at DVS = 1.5001		0.02			3
at DVS = 2		0.02			3

[a] mean air daily temperature.
[b] development stage code (0: emergence; 1: flowering; 2: maturity).
[c] minimum air daily temperature.
[d] 1: adapted from van Heemst (1988); 2: Ceglar et al. (2011); 3: JRC (2012).

Appendix D. WOFOST parameters used for sunflower and statistical settings used for sensitivity analysis (SA). Parameters with the field "Value" populated were not used for SA.

Parameter	Units	Value	Mean	Stand. dev.	Source[d]
Base temperature for emergence (TBASEM)	°C	6			1, 2
Maximum effective temperature for (TEFFMX)	°C	30			1
Thermal sums to reach emergence (TSUMEM)	°C-d	80			1
Daily increase in temperature sums (DTSMTB) at Tavg[a] = 0	°C;°C-d	0			1, 2
at Tavg = 2		0			1, 2
at Tavg = 18		16			1, 2
at Tavg = 40		38			1, 2
Thermal sums from emergence to anthesis (TSUM1)	°C-d	1600			1
Thermal sums from anthesis to maturity (TSUM2)	°C-d	1000			1
Leaf area index at emergence (LAIEM)	ha ha^{-1}		0.005	0.000265	1, 2
Maximum relative increase in leaf area index (RGRLAI)	ha ha^{-1} $°C^{-1}$ d^{-1}		0.029	0.00147	1–3, 4
Specific leaf area (SLATB) at DVS[b] = 0	-; ha kg^{-1}		0.003	0.00015	1, 2, 4
at DVS = 1			0.002	0.00011	1, 2, 4
at DVS = 2.00		0.002			1, 2, 4
Specific pod area (SPA)	ha kg^{-1}	0			1
Specific stem area (SSATB) at DVS = 0	ha kg^{-1}	0			1
at DVS = 2		0			1
Life span of leaves growing at 35 °C (SPAN)	D		30	1.5	1
Base temperature for leaf aging (TBASE)	°C		4.5	0.225	1, 2
Extinction coefficient for diffuse light (KDIFTB) at DVS = 0	-;-		0.8	0.04	1, 2, 5
at DVS = 2			0.8	0.04	1, 2, 5
Light use efficiency single leaf (EFFTB) at Tavg = 0	kg		0.442	0.0221	1
at DVS = 40	ha^{-1} h^{-1} J^{-1} m^2 s		0.442	0.0221	1
Maximum CO_2 assimilation rate (AMAXTB) at DVS = 0	-;kg ha^{-1} h^{-1}		43	2.15	1, 6, 7

at DVS = 1.5			32.5	1.625	1, 6, 7
at DVS = 2			15	0.75	1, 6, 7
Reduction factor of AMAX (TMPFTB) at Tavg = 0	°C;-	0			1, 8
at Tavg = 10			0.5	0.025	1, 2, 8
at Tavg = 20		1			1, 8
at Tavg = 30		1			1, 8
at Tavg = 35			0.75	0.0375	1, 8
at Tavg = 40		0.5			1, 8
Reduction factor of AMAX (TMNFTB) at Tmin[c] = 0	°C;-	0			1
at Tmin = 3		1			1
Efficiency of conversion into leaves (CVL)	kg ka^{-1}		0.697	0.0348	1
Efficiency of conversion into storage organs (CVO)	kg ka^{-1}		0.695	0.0347	1
Efficiency of conversion into roots (CVR)	kg ka^{-1}		0.75	0.0375	1
Efficiency of conversion into stems (CVS)	kg ka^{-1}		0.69	0.0345	1
Rel. incr. in respiration rate per 10 °C (Q10)	–		2	0.1	1
Rel. maintenance respiration rate for leaves (RML)	kg kg^{-1} d^{-1}		0.031	0.00155	1
Rel. maintenance respiration rate for storage organs (RMO)	kg kg^{-1} d^{-1}		0.012	0.000575	1
Rel. maintenance respiration rate for roots (RMR)	kg kg^{-1} d^{-1}		0.01	0.0005	1
Rel. maintenance respiration rate for stems (RMS)	kg kg^{-1} d^{-1}		0.015	0.000745	1
Reduction factor for senescence (RFSETB) at DVS = 0	-;-	1			1
at DVS = 2		1			1
Partitioning to roots (FRTB) at DVS = 0	-;kg kg^{-1}		0.5	0.025	1
at DVS = 0.5			0.325	0.0162	1
at DVS = 1		0			1
at DVS = 2		0			1
Partitioning to leaves (FLTB) at DVS = 0	-;kg kg^{-1}		0.5	0.025	1
at DVS = 0.8			0.2	0.01	1
at DVS = 1		0			1
at DVS = 2		0			1
Partitioning to storage organs (FOTB) at DVS = 0	-;kg kg^{-1}	0			1
at DVS = 1		0			1
at DVS = 1.2			0.739	0.0369	1
at DVS = 1.4			0.869	0.0434	1
at DVS = 2		1			1
Partitioning to stems (FSTB) (function of DVS)	-;kg kg^{-1}	Derived as 1–(FLTB + FOTB)			
Relative death rate of roots (RDRRTB) at DVS = 0	-;kg kg^{-1} d^{-1}	0			1
at DVS = 1.5		0			1
at DVS = 1.5001		0.02			1
at DVS = 2		0.02			1
Relative death rate of stems (RDRSTB) at DVS = 0	-;kg kg^{-1} d^{-1}	0			1
at DVS = 1.5		0			1
at DVS = 1.5001		0.02			1
at DVS = 2		0.02			1

[a] mean air daily temperature.
[b] development stage code (0: emergence; 1: flowering; 2: maturity).
[c] minimum air daily temperature.
[d] 1: adapted from Todorovic et al. (2008); 2: Archontoulis et al. (2011); 3: Hall et al. (1995); 4: Trápani et al. (1999); 5: Casadebaig et al. (2011); 6: Zahoor et al. (2011); 7: Steduto et al. (2000); 8: Paul et al. (1990).

Appendix E. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ecolmodel.2017.11.003.

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